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Epidemiology in R
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 References
Esker, P.D., A.H. Sparks, L. Campbell, Z. Guo, M. Rouse, S.D. Silwal, S. Tolos,
B. Van Allen, and K.A. Garrett, 2008. Ecology and Epidemiology in R: Disease
Forecasting. The Plant Health Instructor. DOI:10.1094/PHI-A-2008-0129-01.
Ecology and Epidemiology in R: Disease Forecasting
Disease Forecasting and Validation
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Student Learning Goals
After completion of this module.
  Students will understand:
    the importance of disease forecasting systems for plant pathology,
    the current methods being applied to plant disease forecasting systems,
    the practical limitations of plant disease forecasting systems.
  Students will acquire these skills:
    apply R-code that illustrates different disease forecasting methods,
    modify R-code to run examples,
    interpret disease forecasting output.
We would appreciate feedback for improving this paper and information about how
it has been used for study and teaching. Please send your feedback to
kgarrett@ksu.edu. Please include the following text in the e-mail subject line,
"Feedback on R Modules", to make sure your comments are received. Plant disease
forecasting systems (synonym: plant disease warning systems) have been developed
to help growers make economic decisions about disease management (Agrios 2004).
Plant disease forecasting systems may support a producer's decision-making
process with regard tothe costs and benefits of pesticide applications, which
  propagation material or seed stock to purchase, and whether to plant a
  specific crop in an area (Agrios 2004). The principle behind plant disease
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forecasting systems is to determine the risk that a disease will occur, or that

What defines a successful plant disease forecasting system? Campbell and Madden

biological and environmental data), simplicity (the simpler the system, the

the intensity of the disease will increase (Campbell and Madden 1990).

(1990) outlined several attributes, including:reliability (use of sound

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more likely it will be applied and used by producers), importance (the disease is of economic importance to the crop, but sporadic enough that the need for treatment is not a given), usefulness (the forecasting model should be applied when the disease and/or pathogen can be detected reliably), availability (necessary information about the components of the disease triangle should be available), multipurpose applicability (monitoring and decision-making tools for several diseases and pests should be available), and cost effectiveness (forecasting system should be cost affordable relative to available disease management tactics).

For an excellent introduction to the epidemiological concepts behind plant disease management, including reducing initial inoculum and/or controlling apparent infection rate, see Arneson's simulation exercise in the Plant Health Instructor (http://www.apsnet.org/edu.../Simulation.htm). Plant disease forecasting systems often provide information about how a grower's management decisions can help to avoid initial inoculum or to slow down the rate of an epidemic. These two concepts are important because they often differentiate the risk for a monocyclic disease (having only one cycle of infection) versus polycyclic disease, where there are multiple infection cycles, and a forecasting system can be used to time appropriate management tactics, such as a foliar fungicide application (Madden et al. 2007). It should be noted that some plant disease forecasts focus both on avoiding initial inoculum and also on reducing the rate of the epidemic during the season (see below). Many plant disease forecasting systems have emphasized forecasts based on the following principles (with examples) (Agrios 2004; Campbell and Madden 1990):

Forecasts based on measures of initial inoculum or disease, example: Stewart's disease of corn (http://www.apsnet.org/edu.../StewartsWilt/default.htm)
Forecasts based on favorable weather conditions for development of secondary inoculum, example: Late blight of potato

 $(\parbox{$http://www.apsnet.org/edu.../LateBlight/default.htm} \parbox{$and$} \$ 

http://www.apsnet.org/edu.../topics/late\_blight/)

Forecasts based on both initial and secondary inoculum, example: Apple scab (http://www.apsnet.org/edu.../AppleScab/default.htm and

http://www.apsnet.org/edu.../topics/applescab/)

An example of a multiple disease/pest forecasting system is the EPIdemiology, PREdiction, and PREvention (EPIPRE) system developed in the Netherlands for winter wheat that focused on multiple pathogens (Reinink 1986).

Current examples of plant disease forecasting providing daily information on-line are available for two important plant diseases: Fusarium head blight of wheat (www.wheatscab.psu.edu) and Asian soybean rust (www.sbrusa.net). Both systems provide background information on the disease, current management recommendations, as well as disease forecast information based on host, pathogen, and environmental factors important for making an accurate forecast. The successful development of a plant disease forecasting system also requires the proper validation of a developed model. There is increased interest among plant disease modelers and researchers to improve producer profitability through validation based on quantifying the cost of a model making false predictions (positive and/or negative). Yuen (http://www.apsnet.org/edu.../DDR/default.htm) discusses this issue in his article, 'Deriving Decision Rules'. As pointed out by Yuen, this methodology is not necessarily a new concept, as historical systems, such as the Mills rules for apple scab, or those used for potato late blight and Alternaria leaf blight of carrots, were developed using prediction rules for plant disease management. An economic validation of a plant disease forecasting system requires the examination of two false predictions:false positive predictions, in which a forecast was made for a disease when in fact no disease was found in a location, and false negative predictions, in which a forecast was made for a disease not to occur when in fact the disease was

found (see Table 2 of Yuen 2006). These two types of false predictions may have different economic effects for producers (Madden 2006). Lastly, the range of disease forecasting models has expanded to include a Bayesian statistical approach. This information is beyond the scope of this exercise and the interested reader is referred to the discussions of Bayesian approaches found in Mila et al. (2003), Yuen (2006), and Madden (2006). Throughout the rest of this document, an introduction to plant disease forecasting is presented through examples, many of which use the R programming environment (Garrett et al. 2007; R Development Core Team). A brief introduction to some of the mathematical/statistical approaches that have been used for developing plant disease forecasting systems is presented, followed by an introduction to how using rainfall and temperature may be applicable for developing a forecast model, and finally, four case studies are presented that highlight the following: modeling the generic risk of infection due to a plant pathogen, use of differential equations to model the population dynamics of sugar beet cyst nematodes in order to understand long-term changes in nematode density, and developing a model that increases the accuracy of an existing forecast model through new information on the percentage of mature pseudothecia.

Next, Mathematical Concepts for Disease Forecasting